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A Dynamic Panel Data Approach to the Forecasting of the GDP of German Länder

Corrected Version

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IMPRESSUM

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A dynamic panel data approach to the forecasting of the GDP of German Länder[¶]

Konstantin A. Kholodilin[*] Boriss Siliverstovs[**] Stefan Kooths[§]

Corrected version

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Abstract

In this paper, we make multi-step forecasts of the annual growth rates of the real GDP for each of the 16 German Länder (states) simultaneously. Beside the usual panel data models, such as pooled and fixed-effects models, we apply panel models that explicitly account for spatial dependence between regional GDP. We find that both pooling and accounting for spatial effects helps substantially improve the forecast performance compared to the individual autoregressive models estimated for each of the Länder separately. More importantly, we have demonstrated that effect of accounting for spatial dependence is even more pronounced at longer forecasting horizons (the forecast accuracy gain as measured by the root mean squared forecast error is about 9% at 1-year horizon and exceeds 40% at 5-year horizon). Hence, we strongly recommend incorporating spatial dependence structure into regional forecasting models, especially, when long-term forecasts are made.

Keywords: German Länder; forecasting; dynamic panel model; spatial autocorrelation.

JEL classification: C21; C23; C53.

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1 Introduction

The current political and economic situation in Europe can be characterized by two major trends. On the one hand, political and especially economic integration on the international level is taking place. On the other hand, the regions, of which nations are comprised, are gaining in importance and autonomy. Hence, there is an increased need for reliable forecasts in order to support decision-making processes at the regional level.

This is particularly true for a federal country like Germany, where regional heterogeneity primarily manifests itself in the distinction between the Eastern and Western Länder (singular Land) due to the legacy of the past as well as in substantial differences in the economic structure within each group. This implies that regional forecasts might diverge from the forecasts made for the whole country, which hence cannot serve as a meaningful guide for decision making at the regional level.

In this paper, we forecast the annual growth rates of GDP for each of the 16 German Länder. To the best of our knowledge, this is the first attempt in the literature that addresses this question for all German Länder simultaneously as most of the studies attempt to forecast German GDP on the aggregate level. These studies include Langmantel (1999), Hinze (2003), Dreger and Schumacher (2004), Mittnik and Zadrozny (2004), Kholodilin and Siliverstovs (2005), and Schumacher (2005), among others, who use several variants of the forecasting methodology of Stock and Watson (2002) based on diffusion indices in order to predict the developments in the German GDP. At the same time, there are two studies that construct forecasts for the individual German Länder, Bandholz and Funke (2003) and Dreger and Kholodilin (2006) who forecast the GDP of Hamburg and of Berlin, respectively, again, using the diffusion indices.

The fact that GDP data for individual German Länder are not available on a quarterly basis severely reduces the post-re-unification data base to 16 annual observations for the period from 1991 to 2006. This may explain the small number of studies aiming at forecasting German GDP on the Länder level.

In this paper, we circumvent the problem of data collection for each regional entity by pooling the annual growth rates of GDP into a panel and correspondingly utilizing panel data models for forecasting. The advantages of such a pooling approach for forecasting have been widely demonstrated in a series of articles for diverse data sets such as Baltagi and Griffin (1997); Baltagi et al. (2003) — for gasoline demand, Baltagi et al. (2000) — for cigarette demand, Baltagi et al. (2002) — for electricity and natural gas consumption, Baltagi et al.

(2004) — for Tobin's q estimation, and Brücker and Siliverstovs (2006) — for international migration, among others.

In addition to pooling, accounting for spatial interdependence between regions may prove beneficial for the purposes of forecasting. Spatial dependence implies that due to spillover effects (e.g., commuter labor and trade flows). Neighboring regions may have similar economic performance and hence the location matters. However, the number of studies that illustrate the usefulness of accounting for (possible) spatial dependence effects across cross sections in the forecasting exercise is still limited. For example, Elhorst (2005), Baltagi and Li (2006), and Longhi and Nijkamp (2007) demonstrate forecast superiority of models accounting for spatial dependence across regions using data on demand for cigarettes from states of the USA, demand for liquor in the American states, and German regional labor markets, respectively. However, only Longhi and Nijkamp (2007) conduct quasi real-time forecasts for period $t + h$ ($h > 0$) based on the information available in period t. On the other hand, the forecasts made in Elhorst (2005) and Baltagi and Li (2006) are not real-time forecasts, since they take advantage of the whole information set that is available in the forecast period, $t + h$.

Applications of panel data models accounting for spatial effects for the forecasting of regional GDP are even more limited. To our knowledge, there is only one paper treating this issue, namely that of Polasek et al. (2007), who make long-term forecasts of the GDP of 99 Austrian regions, but do not evaluate their accuracy in a formal way.

Thus, the main contribution of this paper is the construction of GDP forecasts for all German Länder simultaneously. Our additional contribution to the literature is that in order to make forecasts of regional GDP we employ panel data models that allow not only for temporal interdependence in the regional growth rates, but also take into account their spatial interdependence. The advantage of our approach is that it is suited to conduct forecasts in the real time. We also demonstrate the usefulness of our approach by formal methods.

The paper is structured in the following way. In section 2 the data are described. Section 3 presents different econometric forecasting models. In section 4 the estimation results are reported, whereas section 5 evaluates the forecasting performance of alternative models. Finally, section 6 concludes.

2 Data properties

For our estimation and forecasting we use annual real GDP data of the 16 German Länder. The data cover the period 1991-2006 and can be downloaded from the webpage of the Statistical Office of Baden-Würtemberg (Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder). The data are seasonally adjusted and expressed in terms of chain indices with the base year 2000.

Before we estimate the models described in Section 3, we take a look at the descriptive statistics of the data under consideration displayed in Table 1. In this table, the basic descriptive statistics of the growth rates of real GDP in form of the mean, maximum, minimum, and the standard deviation are summarized at three levels of aggregation: for all German Länder, separately for the Western Länder group and for the Eastern Länder group as well as for each of the Länder individually.

The specific economic dynamics of the Eastern Länder in the first half of the 1990s reflect the re-unification growth effect that was mainly driven by expansionary government interventions (see Vesper (1998) and Bach and Vesper (2000) for a detailed analysis of fiscal policies during this period). The market-oriented transformation of the formerly centrally planned economy in Eastern Germany and the rebuilding of the infrastructure in the Eastern Länder implied public per capita spending that was far above the Western level from the start and rising until the mid-1990s (from 128% in 1992 to 145% in 1995). This expansionary government program was fuelled by both extensive transfers from West to East (starting at 65 billion DM in 1991 and peaking at 118 billion DM in 1996) and deficit spending in the Eastern Länder whose per capita debt quickly approached the Western levels (within the first 5 years the ratio rose from 11% to 90%). Furthermore, due to tax privileges (like special depreciation allowances) the construction sector boomed in the first decade with the East-West ratio of per capita investment more than doubled from 67% in 1991 to 180% in 1996 (residential construction more than tripled in the same period). The special factors that heavily influenced the catching-up process lost momentum after 1995 (no further increase, but stagnation or even decrease of the indicators). Therefore, we have chosen to split the whole period 1992-2006 into two sub-periods: from 1992 till 1995 and from 1996 till 2006.

In the first sub-period the growth rates of the Eastern Länder were much higher than those of the Western Länder. After 1995, this difference has vanished such that in the second sub-period real GDP growth rates in both groups became very similar. Precise figures on the magnitude of the difference in growth rates of Eastern and Western Länder for the period from 1992 till 1995 can be found in Table 1. In this period, in all Eastern Länder, excluding Berlin, the mean growth rates of real GDP was about 10% per annum, such that the average growth rate computed for all Eastern Länder is 8.7, which is about 17 times higher than the average growth rate of 0.5 reported for the Western Länder in this sub-period. Furthermore, from 1992 till 1995 there were no negative growth rates in any of the Eastern Länder, whereas the Western Länder experienced the negative growth rates of real GDP during this sub-period.

In the second sub-period (from 1996 till 2006), the growth rates of real GDP become more or less similar in both Länder groups. The mean growth rates are of about the same magnitude (0.9 for the Eastern Länder vs 1.4 for the Western Länder), with virtually the same standard deviation of 1.4 and 1.6, respectively.

This marked difference between the magnitude of real GDP growth rates in the Eastern and Western Länder in the first sub-period and the fact that it vanished in the second sub-period prompts us to introduce a step dummy variable in our regression models that takes the value of one in the period from 1992 up to and including 1995 and the value of zero otherwise. Observe that this step dummy is applicable only for the six Eastern Länder as namely for those Länder the properties of real GDP growth rates are drastically different in both sub-periods. As far as the properties of the real GDP growth rates in the Western Länder are concerned, we assume that those did not change over the whole period.

We have chosen to interact this step dummy with the autoregressive coefficient in our regression models in order to account for the fact that the persistence in real GDP growth rates in the Eastern Länder in the first period seems to be much more pronounced than in the second sub-period.

3 Dynamic panel data models

In this section we describe the econometric models that we are using for forecasting the growth rates of real GDP of the German Länder. In these otherwise standard models we include the re-unification boom dummy that takes into account specific macroeconomic dynamics of the Eastern Länder in the first half of the 1990s.

In this paper, we examine a standard set of dynamic panel data (DPD) models starting with individual autoregressive (AR) models, which can be considered as a particular case of DPD models with unrestricted parameters, through fixed-effects models, which impose homogeneity restrictions on the slope parameters, to pooled models, which impose homogeneity restrictions on both intercept and slope parameters. In addition to standard fixed-effects and pooled models, we also consider fixed-effects and pooled models that account for spatial dependence.

As a benchmark model, with which all other models will be compared, we use a linear *individual AR(1)* model (I_{OLS}) and estimate it for each Länder separately:

$$y_{it} = \alpha_i + \beta_{i1} y_{it-1} + \beta_{i2} I_{it} y_{it-1} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma_i^2) \tag{1}$$

where y_{it} is the annual growth rate of real GDP of i-th Land; I_{it} is a step dummy, which from now on will be referred to as a re-unification boom dummy. The dummy is defined as follows:

	1992-1995	1996-2006
Eastern Länder	$I_{it} = 1$	$I_{it} = 0$
Western Länder	$I_{it} = 0$	$I_{it} = 0$

In addition, given the short time dimension of our data, it should be noted that the OLS estimator of the parameters of individual AR(1) models is biased due to insufficient degrees of freedom as pointed out in Ramanathan (1995).

The next model we consider is the *pooled panel* (P_{OLS} or P_{GMM} depending on the estimation method) model:

$$y_{it} = \alpha + \beta_1 y_{it-1} + \beta_2 I_{it} y_{it-1} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{2}$$

which imposes the homogeneity restriction on both intercept and slope coefficients across all the Länder.

An alternative model is the *fixed-effects* (FE_{OLS} or FE_{GMM}) model that allows for region-specific intercepts:

$$y_{it} = \alpha_i + \beta_1 y_{it-1} + \beta_2 I_{it} y_{it-1} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{3}$$

The fixed-effects model represents an intermediate case between the individual (I_{OLS}) and pooled panel (P_{OLS} and P_{GMM}) models. It is not too restrictive as the pooled model, which assumes equal average growth rates in all Länder, and yet allows to take advantage of panel dimension. From the economic point of view, fixed effects capture differences in growth rates between Länder related to their heterogeneous economic structure.

Additionally, we consider the following two types of models that account for spatial correlation that might exist between the Länder. One may expect to find the dynamic (stagnating) Länder being the neighbors of dynamic (stagnating) Länder due to cross-border spillovers (commuter labor and trade flows).

The spatial dependence is accounted for using an $N \times N$ matrix of spatial weights W, which is based on the existence of common borders between the Länder[1]. The typical element of this matrix, w_{ij}, is equal to 1 if two corresponding Länder have a common border, and 0 otherwise. All the elements on the main diagonal of matrix W are equal to zero. The constructed weights matrix is normalized such that all the elements in each row sum up to one.

First, we model the spatial dependence by means of spatial lags of the dependent variable. We examine both pooled and fixed-effects versions of this model. **The *pooled spatial Durbin* model (P^{SDM}_{MLE})** can be written as follows:

$$y_{it} = \alpha + \beta_1 y_{it-1} + \beta_2 I_{it} y_{it-1} + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{4}$$

The *fixed-effects spatial Durbin* model (FE^{SDM}_{MLE}) is

$$y_{it} = \alpha_i + \beta_1 y_{it-1} + \beta_2 I_{it} y_{it-1} + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{5}$$

where ρ is the spatial autoregressive parameter and N is the number of Länder.

The second type of models addresses spatial correlation through a spatial autoregressive error structure, as suggested by Elhorst (2005). Again, we distinguish between pooled and fixed-effects models. Due to their specific nature, those models are estimated by the Maximum Likelihood method. The *pooled spatial error* model

[1] We also have considered a matrix of spatial weights based on the distance between the capitals of the Länder. Following Baumont et al. (2002) we constructed four distance-decay weights matrices depending on four different distance cutoff values: first quartile, median, second quartile, and maximum distance. However, the forecast accuracy of the models based on these weights matrices was generally inferior to that of the models with a weights matrix based on common borders. Therefore, in order to save space we chose not to report the corresponding results but we make them available upon request.

(P^{SEM}_{MLE}) has the following form:

$$y_{it} = \alpha + \beta_1 y_{it-1} + \beta_2 I_{it} y_{it-1} + u_{it} \quad u_{it} = \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{6}$$

The *fixed-effects spatial error* model (FE^{SEM}_{MLE}) can be expressed as:

$$y_{it} = \alpha_i + \beta_1 y_{it-1} + \beta_2 I_{it} y_{it-1} + u_{it} \quad u_{it} = \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{7}$$

where λ is the coefficient of spatial error autoregression.

We have estimated I_{OLS}, P_{OLS}, and FE_{OLS} using the OLS method. It is known from the literature that in the context of dynamic panel data models the OLS estimator is subject to simultaneous equation bias. In order to address this problem we have used the GMM estimator of Arellano and Bond (1991) to estimate the fixed-effects model without spatial autoregressive lags. Notice that the GMM estimator uses the first-difference transformation, which omits the time-invariant variables (in our case, the Länder-specific intercepts). These were recovered using the following two-step procedure. In the first step, the slope parameters are estimated using the first differences of the data. In the second step, the estimated parameters are plugged into the equation for the levels of data and the fitted values are calculated. The fixed effects for the FE_{GMM} model are obtained as the Länder-specific averages of difference between actual and fitted values.

Although from the theoretical perspective, the GMM estimators should be preferred to the OLS estimators when applied to dynamic panels with small time dimension, in what follows we use the OLS estimators, since in the forecasting context a biased but stable estimator may still deliver a more accurate forecasting performance than an unbiased but unstable one[2].

The remaining P^{SDM}_{MLE}, FE^{SDM}_{MLE}, P^{SEM}_{MLE} and FE^{SEM}_{MLE} models were estimated using the Maximum Likelihood method as implemented in the Matlab codes of Paul Elhorst.

[2]We thank an anonymous referee for pointing this out.

4 Estimation results

The estimates of the temporal and spatial autoregressive coefficients of all the models are presented in Table 2. At first, we report a summary of the estimates of the temporal autoregressive coefficient $\widehat{\alpha}_1$ obtained for a model estimated for each Land separately. The results of this exercise reveal quite large heterogeneity in the obtained values. For all 16 Länder considered, the minimum value of the autoregressive coefficient estimate is -0.186 and the maximum is 0.230, while the median value is 0.052.

We also report a summary of the estimates of the interaction between the re-unification boom dummy and the growth rates in Eastern regions, $\widehat{\beta_2}$, computed in the regression for each Eastern Land. The magnitudes of the corresponding estimates lie in the interval from 0.379 to 0.780 with a median value of 0.647. Such values of the estimated coefficient support our observation — made earlier in Section 2 — that the persistence in real GDP growth rates in the Eastern Länder was much higher during the period from 1992 till 1995 than that during the period from 1996 till 2006.

Note that the individual autoregressive models seem to provide a rather poor fit to the data as the values of the R^2 often lie near zero. The corresponding median is 0.038. This is most likely due to the rather short period used in the estimation as well as the rather low persistence in the real GDP growth rates for the majority of observations.

The next two columns of Table 2 contain the estimation results obtained for the pooled model (equation 2) and for the fixed-effects model (equation 3) using OLS. For the P_{OLS} model, the estimated value of the autoregressive coefficient is 0.162, which is significant at the 1% level, whereas for the FE_{OLS} model the corresponding value is 0.064 and is significant at the 5% level.

The value of the estimate of the interaction term between re-unification boom dummy and growth rates in Eastern Länder, $\widehat{\beta_2}$, is 0.589 and 0.653 for the pooled and the fixed-effects models, respectively. It is significant even at the 1% level in both cases. Thus, our estimation results are concordant with those obtained from the individual autoregressions that the persistence in growth rates of real GDP in the Eastern Länder was much higher during 1992-1995 than during 1996-2006.

In the fixed-effects FE_{GMM} model estimated by GMM, the autoregressive coefficient is much lower in absolute magnitude and is very close to zero. In contrast, the coefficient of the re-unification boom dummy is of similar magnitude compared to the models estimated by OLS. The appropriateness of this GMM estimator is illustrated by the following specification tests. The Sargan test has a value of 15.44 with a p-value of 1.000, which implies that the null of the instruments' validity cannot be rejected. The significance of the AR(1) test (test statistic -2.482, p-value 0.013) and insignificance of the AR(2) test (test statistic -1.487, p-value 0.137) suggest that the assumption of serially uncorrelated errors is not violated.

Finally, the last four columns of Table 2 contain the parameter estimates of the models that allow for spatial effects. The first two models are spatial Durbin models. The estimates of the autoregressive parameters and the interaction term between re-unification boom dummy and growth rates in Eastern regions for these models are quite similar to those obtained for the models without spatial effects. In addition, the estimates of spatial autoregressive coefficients, $\widehat{\rho}$, of the pooled and fixed-effects models are 0.097 (p=0.110) and 0.119 (p=0.062), respectively. Nevertheless, for the forecasting purposes, Elhorst (2005) recommends using the models that account for spatial dependence even if spatial autocorrelation coefficient is not significantly different from zero.

The last two models, P^{SEM}_{MLE} and FE^{SEM}_{MLE}, are those with spatially correlated errors. The estimates of the autoregressive and interaction term between re-unification boom dummy and growth rates in Eastern Länder parameters are close to those obtained in the corresponding panel models with and without spatial effects estimated by OLS. In contrast to the spatially autoregressive models, the spatial error models point to a strong positive and statistically significant spatial correlation as measured by the coefficient λ. Indeed, $\widehat{\lambda}$ takes values of 0.607 and 0.577, respectively, depending on whether we allow for fixed effects or not. Therefore, one would expect that accounting for spatial effects using this type of model will result in an increased forecasting accuracy compared to the models without spatial effects.

To summarize, on the basis of our estimation results we conclude the following. First, the growth rates of real GDP of the German Länder exhibit rather low temporal dependence, except for the period from 1992 till 1995, when the Eastern Länder enjoyed exceptionally high growth rates. Our interaction term between re-unification boom dummy and growth rates in Eastern regions introduced to capture this effect turns out to be positive and highly significant in all models that we considered in this paper. Second, the growth rates of real GDP exhibit substantial spatial dependence in the current period. Hence, it remains to check whether allowance for this spatial dependence will result in improved forecasts of regional GDP growth rates.

5 Forecasting performance

For each model we forecast recursively the h-year growth rates of real GDP, $\Delta^h y_{i,t+h} = y_{i,t+h} - y_{it}$ for $h = 1, 2, \ldots, 5$ for all 16 Länder over the forecasting period encompassing 5 years from 2002 up to 2006. This procedure gives us $(5 - (h-1)) \times N$ forecasts for the h-year growth rate.

For each model, the parameter estimates were obtained using an expanding window of observations. Thus, the first estimation period is 1993-2001, based on which the forecasts of $\Delta^1 y_{i,2002}, \Delta^2 y_{i,2003}, \ldots, \Delta^5 y_{i,2006}$ are made. Next, the model is re-estimated for the period 1993-2002 and the forecasts $\Delta^1 y_{i,2003}, \Delta^2 y_{i,2004}, \ldots, \Delta^4 y_{i,2006}$ are computed, etc.

For all models, except spatial Durbin models, the forecasts were made in a standard way. The forecasts of the spatial Durbin models are conducted using the two-step procedure[3]. In order to illustrate this procedure, it is worthwhile re-writing the spatial Durbin models (4) and (5) in the following matrix form for the pooled:

$$\mathbf{y} = \alpha \boldsymbol{\imath}_{NT} + \beta_1 \mathbf{y}_{-1} + \beta_2 (\mathbf{D} \odot \mathbf{y_{-1}}) + \rho \mathbf{W} \mathbf{y} + \boldsymbol{\varepsilon} \tag{8}$$

for the fixed-effects versions:

$$\mathbf{y} = (\boldsymbol{\imath}_T \otimes \mathbf{I}_N) \boldsymbol{\alpha} + \beta_1 \mathbf{y_{-1}} + \beta_2 (\mathbf{D} \odot \mathbf{y}_{-1}) + \rho \mathbf{W} \mathbf{y} + \boldsymbol{\varepsilon} \tag{9}$$

where $\mathbf{y}$ is a $NT \times 1$ vector of the y_{it} stacked by year and region such that the first N observations refer to the first year, etc. Correspondingly, $\mathbf{y_{-1}}$ is a $NT \times 1$ vector of the $y_{i,t-1}$ stacked by year and region. The matrix $\mathbf{D}$ is a $NT \times 1$ matrix which structure corresponds to the re-unification boom dummy I_{it} reported in Table 3. Then, $(\mathbf{D} \odot \mathbf{y_{-1}})$ denotes the interaction term between the re-unification boom dummy and the growth rates in Eastern regions, where $\odot$ is the Hadamar product, or element-by-element multiplication operator. $\mathbf{I}_N$, $\mathbf{I}_T$, and $\mathbf{I}_{NT}$ are the unit matrices with dimensions $N \times N$, $T \times T$, and $NT \times NT$, respectively. The $NT \times NT$ matrix $\mathbf{W} = \mathbf{I}_T \otimes W$ is the block-diagonal matrix with the $N \times N$ matrix W of spatial weights on its main diagonal, where is $\otimes$ a Kronecker product. $\boldsymbol{\imath}_{NT}$ and $\boldsymbol{\imath}_T$ are the NT and T unit vectors, respectively, such that α and $\boldsymbol{\alpha}$ are correspondingly a common intercept and an $N \times 1$ vector of cross-section specific intercepts in the pooled

[3]The authors thank two anonymous referees for drawing our attention to this forecasting procedure.

and the fixed-effects spatial Durbin models.

The models (8) and (9) can be re-written in the following reduced form:

$$\begin{aligned}(\mathbf{I_{NT}} - \rho\mathbf{W})\mathbf{y} &= \alpha\boldsymbol{\imath}_{NT} + \beta_1\mathbf{y}_{-1} + \beta_2(\mathbf{D}\odot\mathbf{y_{-1}}) + \boldsymbol{\varepsilon} \\ \mathbf{y} &= (\mathbf{I_{NT}} - \rho\mathbf{W})^{-1}[\alpha\boldsymbol{\imath}_{NT} + \beta_1\mathbf{y}_{-1} + \beta_2(\mathbf{D}\odot\mathbf{y_{-1}})] + (\mathbf{I_{NT}} - \rho\mathbf{W})^{-1}\boldsymbol{\varepsilon} \end{aligned} \tag{10}$$

$$\begin{aligned}(\mathbf{I_{NT}} - \rho\mathbf{W})\mathbf{y} &= (\boldsymbol{\imath}_T \otimes \mathbf{I}_N)\boldsymbol{\alpha} + \beta_1\mathbf{y_{-1}} + \beta_2(\mathbf{D}\odot\mathbf{y}_{-1}) + \boldsymbol{\varepsilon} \\ \mathbf{y} &= (\mathbf{I_{NT}} - \rho\mathbf{W})^{-1}[(\boldsymbol{\imath}_T \otimes \mathbf{I}_N)\boldsymbol{\alpha} + \beta_1\mathbf{y_{-1}} + \beta_2(\mathbf{D}\odot\mathbf{y}_{-1})] + (\mathbf{I_{NT}} - \rho\mathbf{W})^{-1}\boldsymbol{\varepsilon} \end{aligned} \tag{11}$$

where only the past values of $\mathbf{y}$ appear on the right-hand side of the equations.

The multi-step ahead forecasts from the spatial Durbin models can now be obtained as follows. First, we estimate the parameters of the models (8) and (9), as outlined above. Second, we use the reduced form equations (10) and (11) in order to generate the forecasts.

The results of our forecasting exercise are reported in Table 3. The forecasting performance is measured by the total root mean square forecast error (Total RMSFE) calculated for all years and over all regions for each forecasting horizon, $h = 1, 2, \ldots, 5$. The individual autoregressive model serves as a benchmark, to which the forecasting performance of all other models is compared. Hence, the relative total RMSFE measures the gains in forecasting accuracy from pooling and from accounting for spatial dependence.

The results of our forecasting exercise further strengthen the evidence previously reported in a number of studies such as Baltagi and Griffin (1997); Baltagi et al. (2003), Baltagi et al. (2000), Baltagi et al. (2002), Baltagi et al. (2004), and Brücker and Siliverstovs (2006), among others, that pooling helps to improve forecast accuracy. As seen, the pooled OLS model produces an RMSFE that is about 9% lower than that reported for the individual AR(1) models. Allowing for the presence of fixed effects, however, does not lead to further improvements in forecast accuracy. The likely reason is that the relatively short time span of our data impedes on a precise estimation of region-specific intercepts. An F-test for the absence of fixed effects does not reject the null hypothesis ($F(15, 208) = 1.091$ with p-value equal 0.366).

Despite their theoretical appeal, the fixed-effects model estimated by GMM produces even poorer forecasting performance. Possible reason is that the GMM has poor finite sample properties, as documented in a number of Monte Carlo studies (see Arellano and Bond (1991), Kiviet (1995), Ziliak (1997), and Alonso-Borrego and Arellano (1999)).

As expected, the application of pooled and fixed-effects models accounting for spatial effects results in a better forecast accuracy compared not only to the benchmark model but also to the pooled and fixed-effects models, which do not take into account spatial effects.

The largest forecast accuracy gain is achieved when the pooled models are used. The best forecast performance is delivered by P^{SEM}_{MLE} closely followed by P^{SDM}_{MLE}. This ranking remains the same over all forecasting horizons. More importantly, the relative forecast accuracy improvement with respect to the benchmark model increases with longer forecasting horizon. For example, at $h = 1$ the ratio of total RMSFE of P^{SEM}_{MLE} and P^{SDM}_{MLE} with respect to that of the benchmark model is 0.906 and 0.908, respectively, which represents forecast accuracy improvement of 9.4% and 9.2%, correspondingly. At the forecasting horizon $h = 5$, this improvement constitutes 40.4% and 36.8%, respectively. The P_{OLS} model is ranked as the third best model where the similar pattern is also observed to somewhat lesser degree — the corresponding relative RMSFE at $h = 1$ is 0.915 and at $h = 5$ is 0.680. Observe that the forecasting accuracy of the pooled models accounting for the spatial dependence also gets larger relatively to the pooled model without spatial effects as forecasting horizon increases. Thus, the ratios of the total RMSFE of the P_{OLS} model with that of the P^{SEM}_{MLE} at the 1-year and the 5-year forecasting horizons are 0.989 and 0.876, respectively.

The fixed-effects models with and without spatial effects can be ranked according to their forecast accuracy as follows: FE^{SDM}_{MLE}, FE^{SEM}_{MLE}, FE_{OLS}, and FE_{GMM}. This ranking remains unchanged across all forecast horizons. Again, the two best models are those accounting for spatial dependence. Their forecasting performance relative to that of the fixed-effects models without spatial effects also tends to increase with longer forecast horizons.

6 Summary

In this paper, we have addressed the forecasting of h-year growth rates of real GDP for of each of the 16 German Länder using dynamic panel data models, $h = 1, 2, \dots, 5$. Based on the results of Bach and Vesper (2000), we account for the exceptional behavior of the Eastern Länder economies during the re-unification boom in the early 1990s.

Our main finding is that pooled models accounting for spatial dependence, P^{SEM}_{MLE} and P^{SDM}_{MLE}, produce the best forecasting accuracy (as measured by the Root Mean Squared Forecast Error) compared to any other model examined in this paper. This finding remains robust across all forecasting horizons. Furthermore, the gain in forecasting performance of these models gets larger with increase in forecasting horizon when compared not only to the benchmark model but also to models that do not account for spatial dependence in growth rates of real GDP. For example, compared to the benchmark model, a gain in forecasting accuracy of the pooled models accounting for spatial effects at $h = 1$ is about 9%, whereas at $h = 5$ it is more than 40%. Similarly, a gain in forecasting accuracy of our best pooled model accounting for spatial effects when compared to the pooled model without spatial effects is about 1% at $h = 1$, whereas at $h = 5$ it is more than 12%.

Two factors must have contributed to this improvement: pooling and accounting for spatial effects. On the one hand, the finding that pooling helps to increase the forecasting accuracy is consistent with the results obtained in Baltagi and Griffin (1997); Baltagi et al. (2003), Baltagi et al. (2000), Baltagi et al. (2002), Baltagi et al. (2004), and Brücker and Siliverstovs (2006), *inter alia*, for diverse data sets. On the other hand, the fact that accounting for spatial effects helps to improve the forecast performance further strengthens conclusions Elhorst (2005) and Longhi and Nijkamp (2007). More importantly, we have demonstrated that effect of accounting for spatial dependence is even more pronounced at longer forecasting horizons. Hence, on the basis of our results, we strongly recommend incorporating spatial dependence structure into regional forecasting models, especially, when long-run forecasts are made.

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Appendix

Table 1: Descriptive statistics of the growth rates of real GDP of the German Länder (%)

Period	1992-1995				1996-2006			
	Min	Mean	Max	St.dev.	Min	Mean	Max	St.dev.
Total all	**-4.4**	**3.6**	**16.5**	**4.9**	**-4.2**	**1.2**	**5.4**	**1.5**
				West Länder				
Baden-Württemberg	-4.3	0.2	2.1	2.6	-0.6	1.8	3.6	1.3
Bayern	-1.8	1.0	2.7	1.7	0.8	2.6	5.3	1.3
Bremen	-2.9	-0.3	1.4	1.6	-0.5	1.4	4.1	1.3
Hamburg	0.4	0.9	1.2	0.3	-4.2	1.0	5.4	2.5
Hessen	-1.8	0.6	1.9	1.4	-1.7	1.2	3.4	1.5
Niedersachsen	-1.0	0.6	2.1	1.3	-0.9	0.9	2.7	1.2
Nordrhein-Westfalen	-2.4	0.4	1.8	1.6	-1.0	1.0	2.3	1.0
Rheinland-Pfalz	-2.9	0.2	1.8	1.9	-1.2	1.2	2.7	1.2
Saarland	-4.4	0.4	3.0	3.0	-1.1	1.9	4.4	1.7
Schleswig-Holstein	-1.0	1.0	2.2	1.2	-1.5	1.0	2.7	1.1
Total West	**-4.4**	**0.5**	**3.0**	**1.9**	**-4.2**	**1.4**	**5.4**	**1.6**
				East Länder				
Berlin	1.1	2.2	3.4	0.9	-1.9	-0.7	1.1	0.9
Brandenburg	7.3	9.8	11.8	1.8	-1.5	1.3	4.0	1.7
Mecklenburg-Vorpommern	7.5	9.8	11.8	1.6	-0.6	0.6	3.3	1.2
Sachsen-Anhalt	7.5	10.2	12.2	1.8	0.1	1.3	2.5	0.9
Sachsen	4.3	9.1	12.4	3.0	-0.2	1.2	2.9	0.9
Thüringen	3.3	11.1	16.5	4.9	0.0	1.9	3.6	1.2
Total East	**1.1**	**8.7**	**16.5**	**4.0**	**-1.9**	**0.9**	**4.0**	**1.4**

Table 2: Estimation results 1993 - 2006

	No spatial effects						With spatial effects			
	I_{OLS} Minimum	I_{OLS} Median	I_{OLS} Maximum	P_{OLS}	FE_{OLS}	FE_{GMM}	P_{MLE}^{SDM}	FE_{MLE}^{SDM}	P_{MLE}^{SEM}	FE_{MLE}^{SEM}
$\widehat{\beta}_1$	-0.186	0.052	0.230	0.162***	0.064**	0.002	0.166**	0.082	0.220***	0.064
$\widehat{\beta}_2$	0.379**	0.647**	0.780***	0.589***	0.653***	0.675***	0.548***	0.603***	0.559***	0.664***
$\widehat{\lambda}$	—	—	—	—	—	—	—	—	0.577***	0.607***
$\widehat{\rho}$	—	—	—	—	—	—	0.097	0.119*	—	—
R^2	0.000	0.038	0.840	0.601	0.630	0.627	0.631	0.686	0.740	0.773

$\widehat{\beta}_1$ denotes the estimate of the temporal autoregressive parameter.
$\widehat{\beta}_2$ denotes the estimate of temporal autoregressive parameter times re-unification dummy.
$\widehat{\lambda}$ denotes the coefficient estimate of the re-unification-boom dummy.
$\widehat{\rho}$ denotes the estimate of the spatial autoregressive parameter.
***, **, * – denotes significance at 1%, 5%, and 10% levels.

Table 3: Forecasting performance, all Länder 2002-2006

h-step ahead forecast	Forecasting accuracy measure	No spatial effects				Spatial effects			
		I_{OLS}	P_{OLS}	FE_{OLS}	FE_{GMM}	P_{MLE}^{SDM}	FE_{MLE}^{SDM}	P_{MLE}^{SEM}	FE_{MLE}^{SEM}
h=1	Total RMSFE	0.0155	0.0141	0.0146	0.0149	0.0140	0.0144	0.0140	0.0145
	Relative RMSFE	1.000	0.915	0.943	0.966	0.908	0.935	0.906	0.937
h=2	Total RMSFE	0.0238	0.0208	0.0223	0.0234	0.0203	0.0219	0.0201	0.0222
	Relative RMSFE	1.000	0.873	0.935	0.980	0.852	0.918	0.841	0.931
h=3	Total RMSFE	0.0308	0.0271	0.0287	0.0303	0.0266	0.0282	0.0263	0.0282
	Relative RMSFE	1.000	0.879	0.930	0.984	0.863	0.913	0.852	0.916
h=4	Total RMSFE	0.0397	0.0310	0.0351	0.0384	0.0293	0.0339	0.0282	0.0343
	Relative RMSFE	1.000	0.782	0.885	0.967	0.740	0.855	0.712	0.865
h=5	Total RMSFE	0.0494	0.0336	0.0399	0.0444	0.0312	0.0384	0.0295	0.0387
	Relative RMSFE	1.000	0.680	0.807	0.898	0.632	0.777	0.596	0.784

Total RMSFE = total root mean squared forecast errors (RMSFE) computed for all the Länder over all years together. Relative RMSFE = total RMSFE of each alternative model divided by that of the benchmark model, for every forecasting horizon h.